



Modelling the impact of new parkrun events: efficiency vs equity

Center for Chronic Disease Research and Policy University of Chicago

Dr Robert Smith | November 2024

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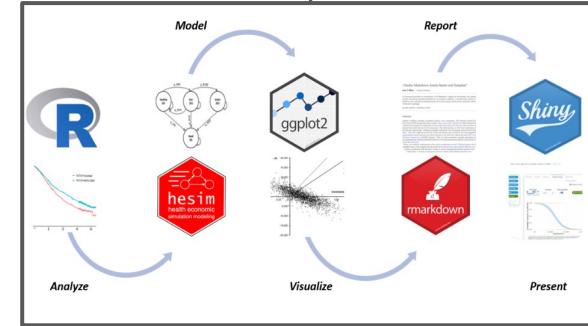
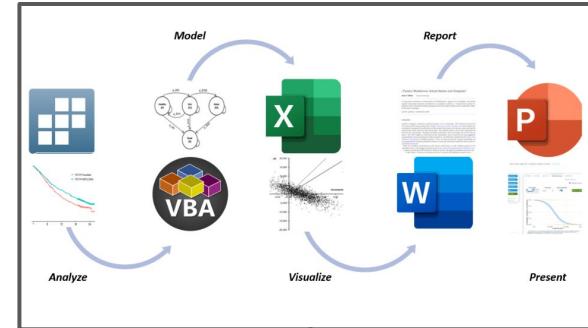
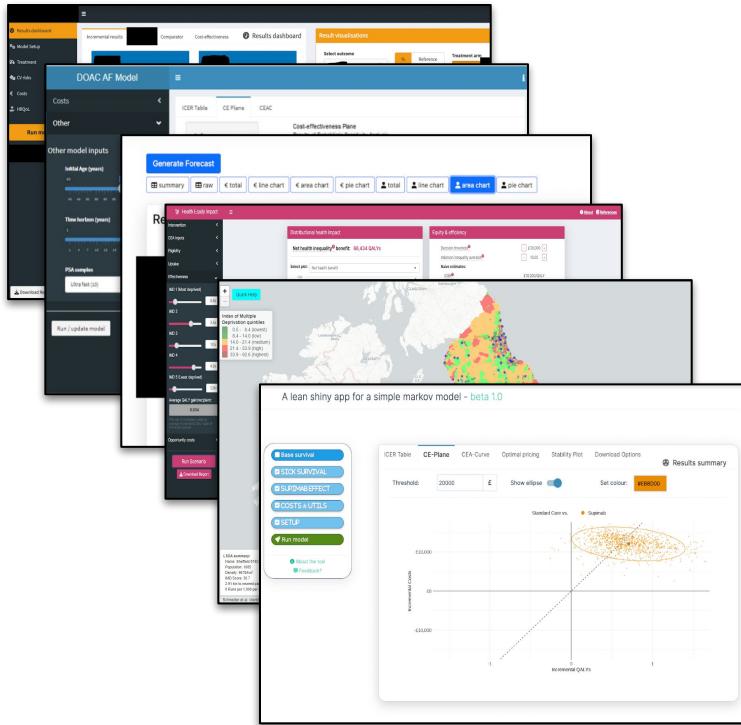
Who am I?



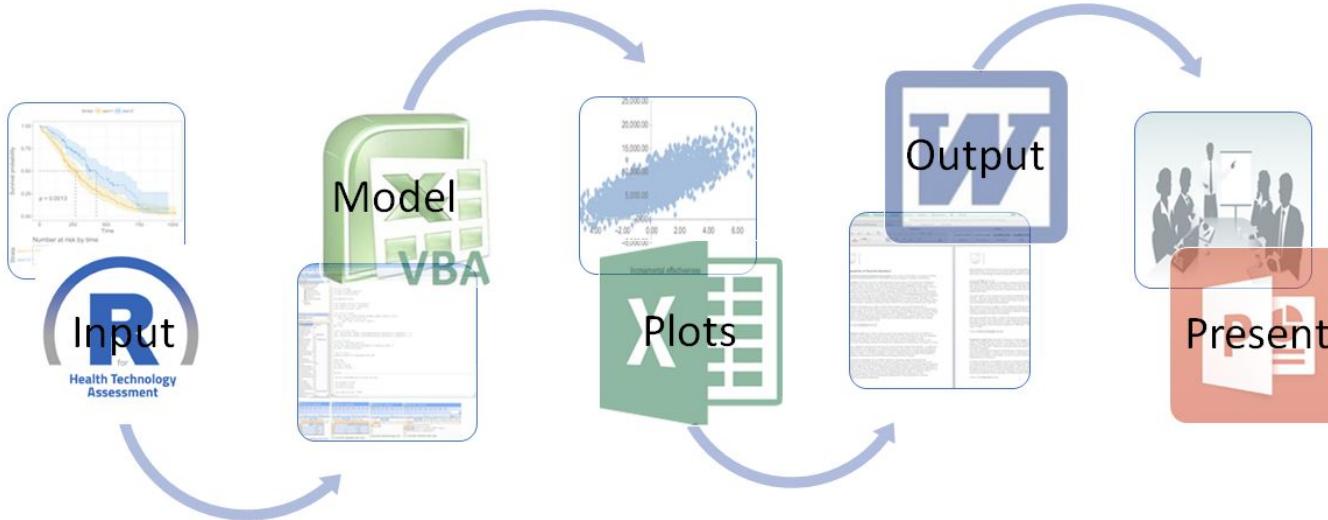
Robert Smith, PhD

- 1) Dark Peak Analytics
- 2) University of Sheffield

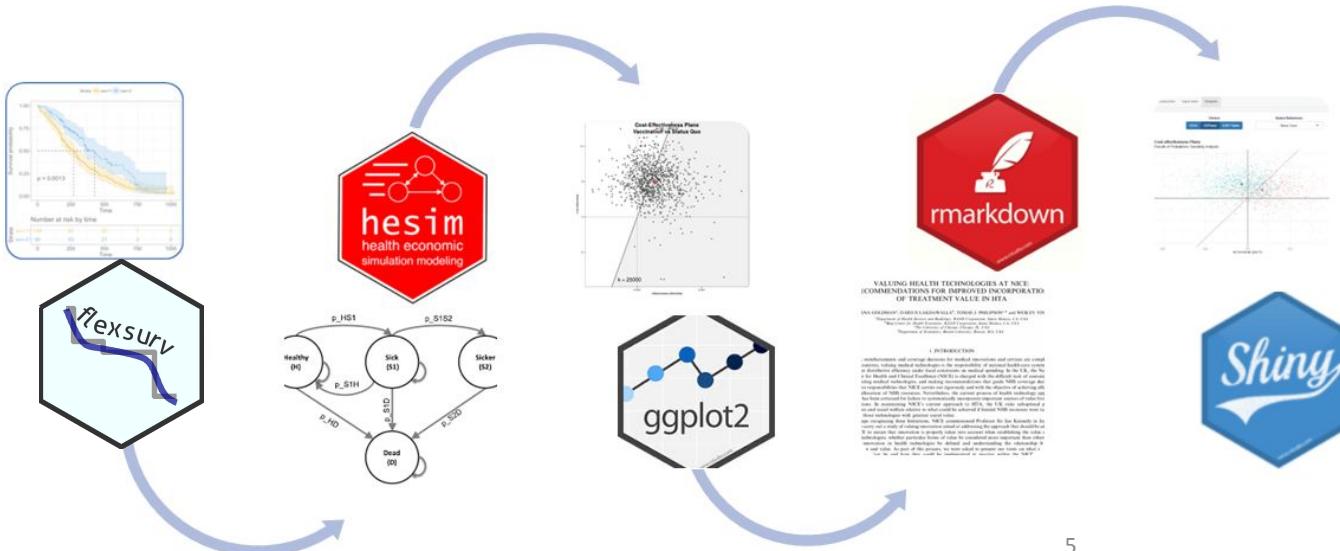
Shifting Health Economics to Script Based Models



Current process



Future process





User-interfaces

Wellcome Open Research

Wellcome Open Research 2020, 5:69 Last updated 05 July 2022

METHOD ARTICLE

View record Making health economic models Shiny: A tutorial

[version 2; peer review: 2 approved]

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Abstract

Health economic evaluation models have traditionally been built in Microsoft Excel, but more sophisticated tools are increasingly being used as model complexity and computational requirements increase. Of all the programming languages, R is most popular amongst health economists. It is a free, open source language, it is well documented and is highly flexible. However, even with an integrated development environment such as R Studio, R lacks a simple point and click user interface and lacks the graphical programming ability. This might make the switch from Microsoft Excel to R seem daunting, and it might make it difficult to directly communicate results with decision makers and other stakeholders.

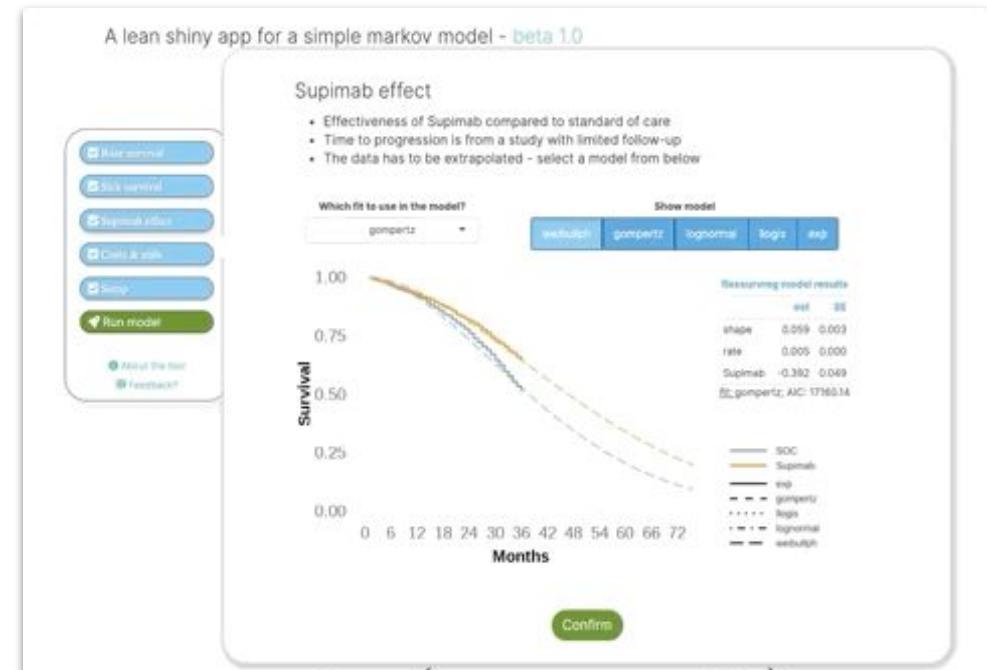
The R package Shiny has the potential to resolve this limitation. It allows programmes to be run via a web browser and can be developed in R and programmed with a lower level user interface. Users can specify their own assumptions about model parameters and run different scenario analyses, which, in the case of regular a Markov model, can be computed within seconds. This paper provides a brief introduction to Shiny and demonstrates how it can be used to build a shiny application. We use a four-state Markov model developed by the Decision Analysis in Health (DARTH) group as a case study to demonstrate main principles and basic functionality.

A more extensive tutorial, all code, and data are provided in a GitHub repository.

Keywords

Health Economics, R, RShiny, Decision Science

Page 1 of 26



<https://darkpeakanalytics.shinyapps.io/sadm-mk2/>

Smith RA and Schneider PP. Making health economic models Shiny: A tutorial. Wellcome Open Res 2020, 5:69
(<https://doi.org/10.12688/wellcomeopenres.15807.2>)



OK - stop talking about yourself!



Research collaboration



The
University
Of
Sheffield.



Dr. Paul Schneider



Dr. Robert Smith

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Background



Background



<https://www.youtube.com/watch?v=ktx4lujARdc&feature=share>

Background

PARTNERSHIP WITH PARKRUN WORTH £3M

Collaboration aims to create 200 new events and boost participants from under-represented groups



12 December 2018



News



Funding





Parkrun research publications

Wellcome Open Research

Wellcome Open Research 2020; 5:1 last updated 05 July 2020



RESEARCH ARTICLE

Does ethnic density influence community participation in mass participation physical activity events? The case of parkrun in England [version 2; peer review: 3 approved]

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Abstract

Background: parkrun has been successful in encouraging people in England to participate in their weekly 5 km running challenges events. However, there is substantial heterogeneity in parkrun participation across different communities in England after controlling for deprivation. More deprived communities have significantly lower participation rates.

Methods: This paper expands on previous findings by incorporating deprivation into the analysis. We used data from the most recent geo-spatial data available through the Office for National Statistics and participants' responses to parkrun survey questionnaires to run Poisson regression models to study the effect of ethnic density on participation rates at the Lower Layer Super Output Level.

Results: Results suggest that ethnic density has a positive effect on lower participation rates. This effect is independent of deprivation.

Conclusions: An opportunity exists for parkrun to engage with these communities and reduce potential barriers to participation.

Keywords: parkrun, Physical Activity, Ethnic Density, Deprivation



Page 1 of 19

2020

2020

2021

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Public Health 2020; 16:6

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BMC Public Health

Open Access

The long-term effect of the coronavirus pandemic on parkrun participation: an interrupted time series analysis

Oscar Rousham¹, Helen Quirk², Elizabeth Goyder³ and Robert A. Smith⁴

Abstract

Background: The growth of parkrun between 2010 and 2019 has been heralded as a success story for public health as a result of its physical activity and wellbeing benefits for participants. However, parkrun was hit immensely from the COVID-19 pandemic – with events in mainland England cancelled from March to May 2020. This study explores the lasting impact of the pandemic on parkrun participation to February 2023, and its implications for the socioeconomic spread.

Methods: This study uses aggregated parkrun weekly finisher data from 32,470 Lower Layer Super Output Areas (LLSAs) in England from January 2010 to February 2023 with Office of National Statistics (ONS) data on population and deprivation. Interrupted time series analysis using segmented Poisson regression models was used to estimate the mean change in parkrun participation and the rate of growth before and after the pandemic. Models were fitted for each index of Multi-dimensional Deprivation (IMD) to explore whether this was influenced by socioeconomic deprivation.

Results: Visualisation and interrupted time series analysis showed a significant and long-term decrease in parkrun participation in the weeks preceding of parkrun events. This was consistent across all IMD quintiles, indicating that the inequalities in parkrun participation according to IMD persisted from the pandemic remained after the period of closure. From March 2020 to February 2023, almost 13 million parkrun finishes are estimated to have occurred relative to what would have occurred in the absence of the pandemic.

Conclusion: The reduction in parkrun participation during the pandemic and following the reopening of events is likely to have negatively impacted wellbeing in would-be participants. Going forwards, policymakers must make the difficult trade-off between the long-term health and social implications of restricting outdoor physical activity events against the benefits associated with a reduction in infectious disease transmission.

Keywords: Parkrun, Physical activity, Socioeconomic deprivations, Ecological model, Interrupted time series

Introduction

Engaging in regular physical activity is linked to a range of health benefits, including the prevention and control of non-communicable diseases [1], along with notable reductions in depression and anxiety [1], as well as an increase in life expectancy [2]. In addition, the percentage of the population falls short of recommended activity levels [1] and there is socioeconomic inequality in leisure time physical activity levels [1, 3, 19]. Elevating

intervention efforts to encourage low-income individuals to participate in physical activity is a key priority [4, 5].

Background: parkrun has been successful in encouraging people in England to participate in their weekly 5 km running challenges events. However, there is substantial heterogeneity in parkrun participation across different communities in England after controlling for deprivation. More deprived communities have significantly lower participation rates.

Methods: This paper expands on previous findings by incorporating deprivation into the analysis. We used data from the most recent geo-spatial data available through the Office for National Statistics and participants' responses to parkrun survey questionnaires to run Poisson regression models to study the effect of ethnic density on participation rates at the Lower Layer Super Output Level.

Results: Results suggest that ethnic density has a positive effect on lower participation rates. This effect is independent of deprivation.

Conclusions: An opportunity exists for parkrun to engage with these communities and reduce potential barriers to participation.

Keywords: parkrun, Physical Activity, Ethnic Density, Deprivation

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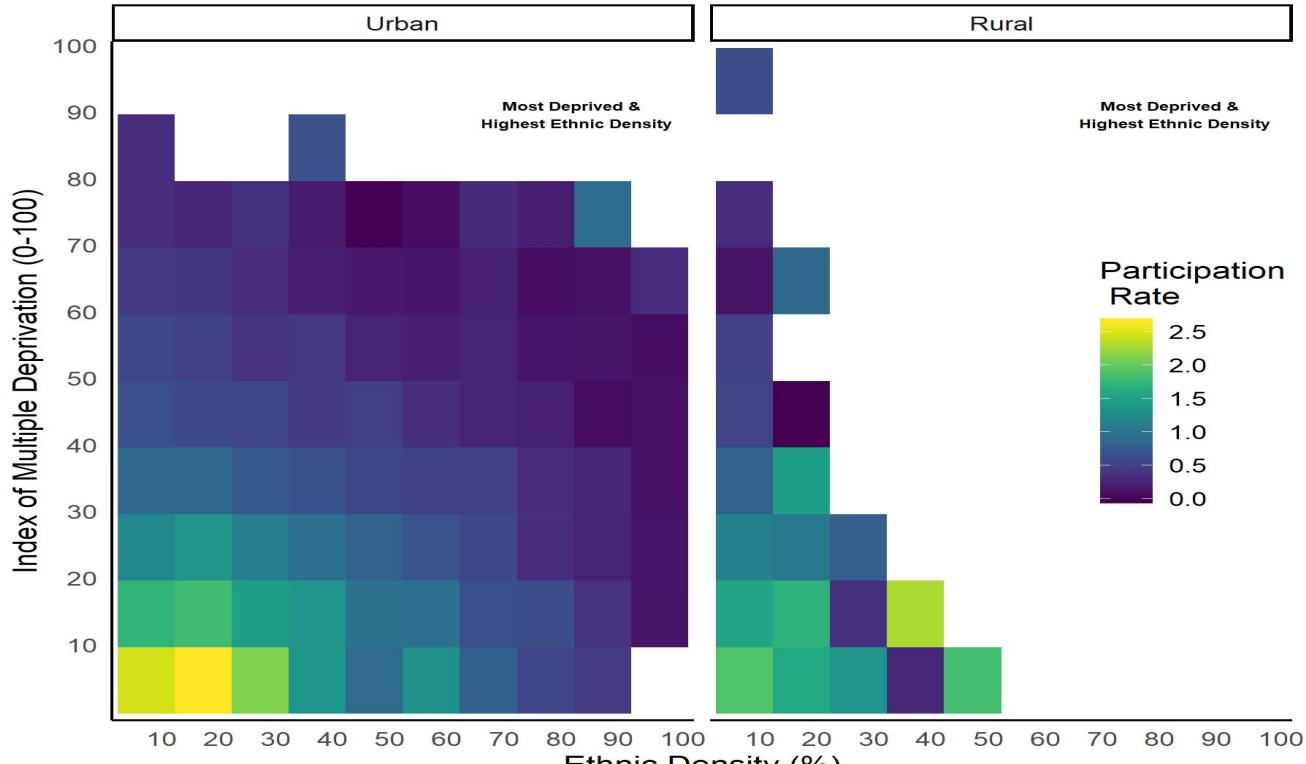


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Ethnicity, Deprivation & Access



Sources: Office for National Statistics and parkrunUK

Longitudinal study - participation & access



Socioeconomic inequalities in distance to and participation in a community-based running and walking activity: A longitudinal ecological study of parkrun 2010 to 2019^{a,b,c,d,e}

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ARTICLE INFO

Keywords:
Parkrun
Physical activity
Socioeconomic deprivation
Ecological study
Relative index of Deprivation

Abstract
Objective: To conduct a longitudinal ecological analysis of the distance to and participation in five weekly community physical activity events (parkrun) in England from 2010 to 2019, and related socioeconomic and ethnic inequalities, to inform policies to support participation in physically active community events.

Methods: We used data from parkrun, a free, weekly, community-based running and walking event, in Lower Output Areas (LOAs) each month from January 2010 to December 2019. We then report the trends in distance to and participation in parkrun by Index of Multiple Deprivation quintile. We also report trends in the Relative Index of Deprivation (RID) and the Index of Multiple Deprivation (IMD) quintiles. We used Poisson regression models to predict trends in IMD level determinants (e.g. deprivation and ethnicity) of parkrun participation between 2010 and 2019, using time-varying covariates.

Results: Mean distance to the nearest parkrun decreased from 34.3 km in 2010, to 4.6 km in 2019. Throughout the period, parkrun events tended to be situated closer to deprived areas compared to less deprived areas. The mean distance to the nearest parkrun increased over the period, with a significant positive trend to linear growth. Participation over the period exhibited a clear socioeconomic gradient, with people from deprived communities having consistently lower participation than the most deprived. Participation rates increased between 2010 and 2013 (H11 Poisson regression model: 189 to 391), and then declined to 291 in 2014 to 2019. The results of the Poisson regression model validate this finding, the coefficients on IMD quintiles were significant (20% most deprived: -0.0001 ; 2: -0.0002 ; 3: -0.0003 ; 4: -0.0004 ; 20% least deprived: -0.0005).

Conclusions: Over the past 10 years, parkrun distance to the nearest parkrun decreased from a mean of 34 km to 5 km. In 2010, there was equality between the least and most deprived areas but by 2017 the distance of the most deprived areas was 29% that of the least deprived. Participation was shown to have increased over the past 10 years, with a significant positive trend. There was a significant positive trend in the IMD quintile and inequality in participation fell dramatically; from 2010 to 2019 participation increased linearly, and inequality in participation fell from 2010 to 2013. Since 2013, participation has been stable, with the most deprived communities, the socioeconomic gradient in participation rates remained high and stable since 2013. Gaining a better understanding of the reasons why parkrun grew so quickly may be useful for other physical activity movements, while further analysis of the relatively lower participation rates in areas with higher

* R.S., P.S. & R.C. are joint funded by the Wellcome Trust Doctoral Training Centre in Public Health, Economics and Decision Science (130902) and the University of Sheffield. H.Q. is funded by an NHR School of Public Health Research (SPHR) post-doctoral funding fellowship. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript. We would like to thank Steve Haake (Head of Analysis at parkrun) and Christopher Wellington (Global Head of Health and Wellbeing at parkrun) for providing area-level parkrun participation data.

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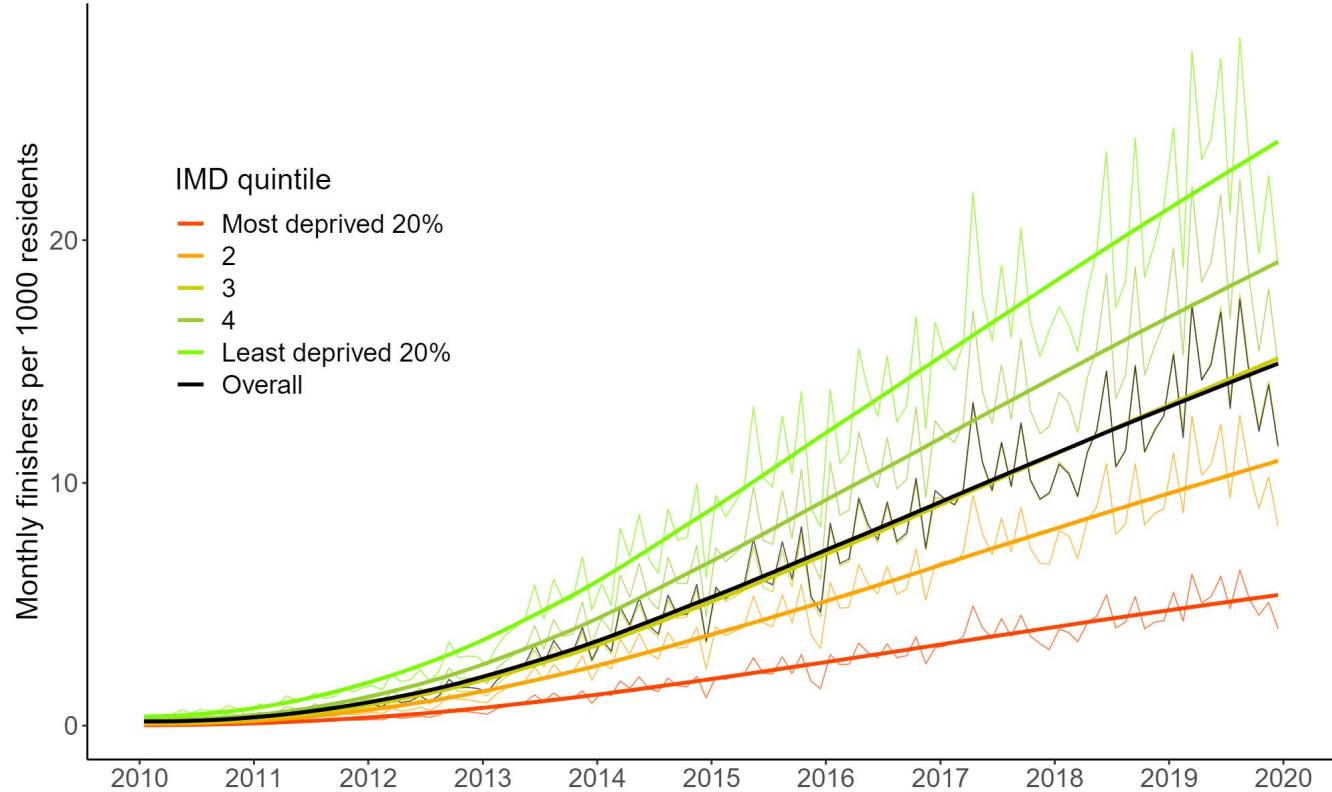
^e Data available from the authors.

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Where should parkrun events be located?

Public Health 103 (2020) 40–53

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Original Research

Multiple deprivation and geographic distance to community physical activity events — achieving equitable access to parkrun in England

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ARTICLE INFO

Objectives: To evaluate geographic access to free weekly outdoor physical activity events ('parkrun') in England, to identify potential locations for proposed communities, and to identify optimal locations for future parkrun events to further increase access.

Study design: This study is a cross-sectional ecological analysis of the socio-economic disparities in parkrun access across England.

Setting: All parkrun events in England.

Methods: We combined geolocation data on all English Lower Layer Super Output Areas and parkrun events to calculate geodesic distances to the nearest event for more than 32,000 communities in England. We used the index of multiple deprivation to measure the socio-economic status of each community and socio-economic deprivation, measured using the index of multiple deprivation. We then used geographic information system spatial analysis to conduct a simple location-allocation analysis to identify optimal locations for proposed parkrun events.

Results: In England, 93% of the population live within 5 km of one of the 405 parkrun events. There is a significant positive correlation between the number of parkrun events and the index of multiple deprivation. Setting up an additional 200 events in optimal locations would improve average access to the nearest parkrun event by 122 km, from 10.2 km to 8.9 km, and would increase the number of people living within 5 km of a parkrun event by 100,000. Over 90% of the English population live within 5 km of a parkrun event, and contrary to our expectation, we find that geographic access is slightly better for those living in more deprived communities. Creating additional events may improve geographic access, but effective strategies will still be required to increase engagement in new and existing events by those living in socio-economically deprived areas.

Conclusion: Over 90% of the English population live within 5 km of a parkrun event, and contrary to our expectation, we find that geographic access is slightly better for those living in more deprived communities. Creating additional events may improve geographic access, but effective strategies will still be required to increase engagement in new and existing events by those living in socio-economically deprived areas.

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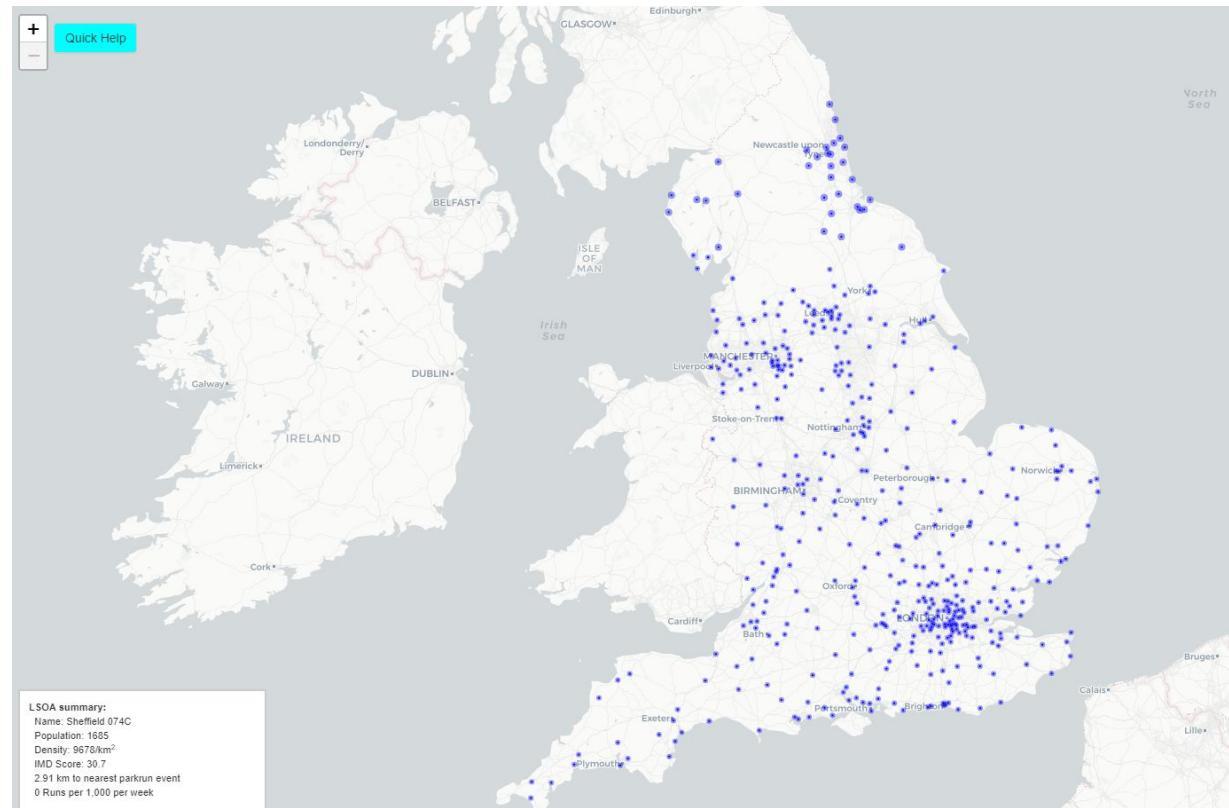
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Introduction

Inufficient physical activity is one of the leading causes of disease and disability worldwide.¹ In the UK, around one in six deaths are due to low levels of physical activity,² which is also a major contributor to health inequalities, as people from low socio-economic backgrounds are both disproportionately likely to be

inactive^{3,4} and be affected by physical inactivity-related diseases,⁵ increasing the physical activity levels of the population is therefore high on the public health agenda. It not only has the potential to improve quality of life, reduce mortality rates and alleviate the burden on social services but also reduce the gap in health inequalities.⁶

However, designing effective health interventions to increase physical activity is a considerable challenge,^{7,8} implementing such interventions in a way that does not increase health inequalities might even be more difficult. Studies have shown that programmes to increase physical activity often fail to reach deprived communities and those most in need, suggesting





Greedy search algorithm

More formally, we define that for any candidate green space location j , the objective function $f(j|E)$ provides the sum of parkrun runs r_i over all LSOA i , weighted by the squared IMD score w_i^2 , given the set of established parkrun event locations $E = \{e_1, e_2, \dots, e_{455}\}$:

$$f(j|E) = \sum_{i=1}^{32844} w_i^2 * r_{ij}$$

In the absence of causal estimates, we use the Poisson regression model specified above to predict the expected number of runs r_{ij} for LSOA i based on its IMD score w_i , its (linear) distance to the nearest parkrun event d_{ij} , and its population p_i . The functional form is given below.

$$E(r_{ij}|w_i, d_{ij}, p_i) = \exp(\beta_0 + \beta_1 * w_i + \beta_2 * d_{ij} + \ln(p_i) + \epsilon)$$

Filling-in the parameter coefficients (see table 3), we derive the following formula:

$$\hat{r}_{ij} = \exp(-5.402 - 0.048 * w_i - 0.082 * d_{ij} + \ln(p_i))$$

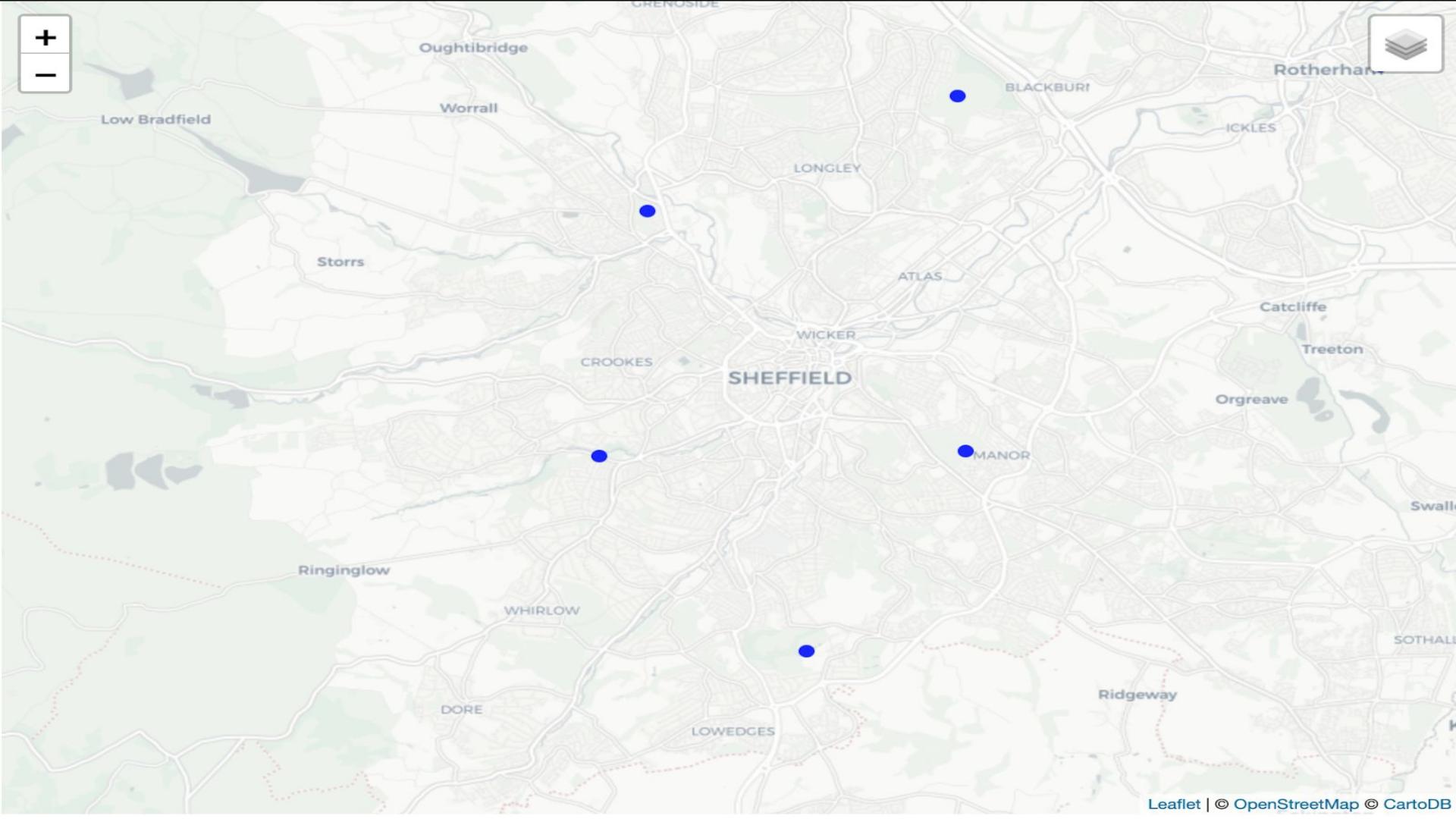
Note that j can have an effect on r_{ij} through d_{ij} : setting up a new event at location j will reduce the distance to the nearest event for some LSOA i . This means, we evaluate the distances from LSOA i to all established parkrun event locations $\{e_1, e_2, \dots, e_{455}\} \in E$, denoted $\overline{l_i e_1}, \overline{l_i e_2}, \dots, \overline{l_i e_{455}}$, and to the candidate green space location j , denoted $\overline{l_j e_i}$, and then take the minimum value, i.e. $d_{ij} = \min(\overline{l_i j}, \overline{l_i e_1}, \overline{l_i e_2}, \dots, \overline{l_i e_{455}})$.

The expected change in the objective function is computed for all candidate locations j in the set of the available green spaces $C = \{c_1, c_2, \dots, c_{2842}\}$, and the location with the maximum value is selected. The selection function is expressed in the following formula:

$$\arg \max_{j \in C} f(j|E)$$

+

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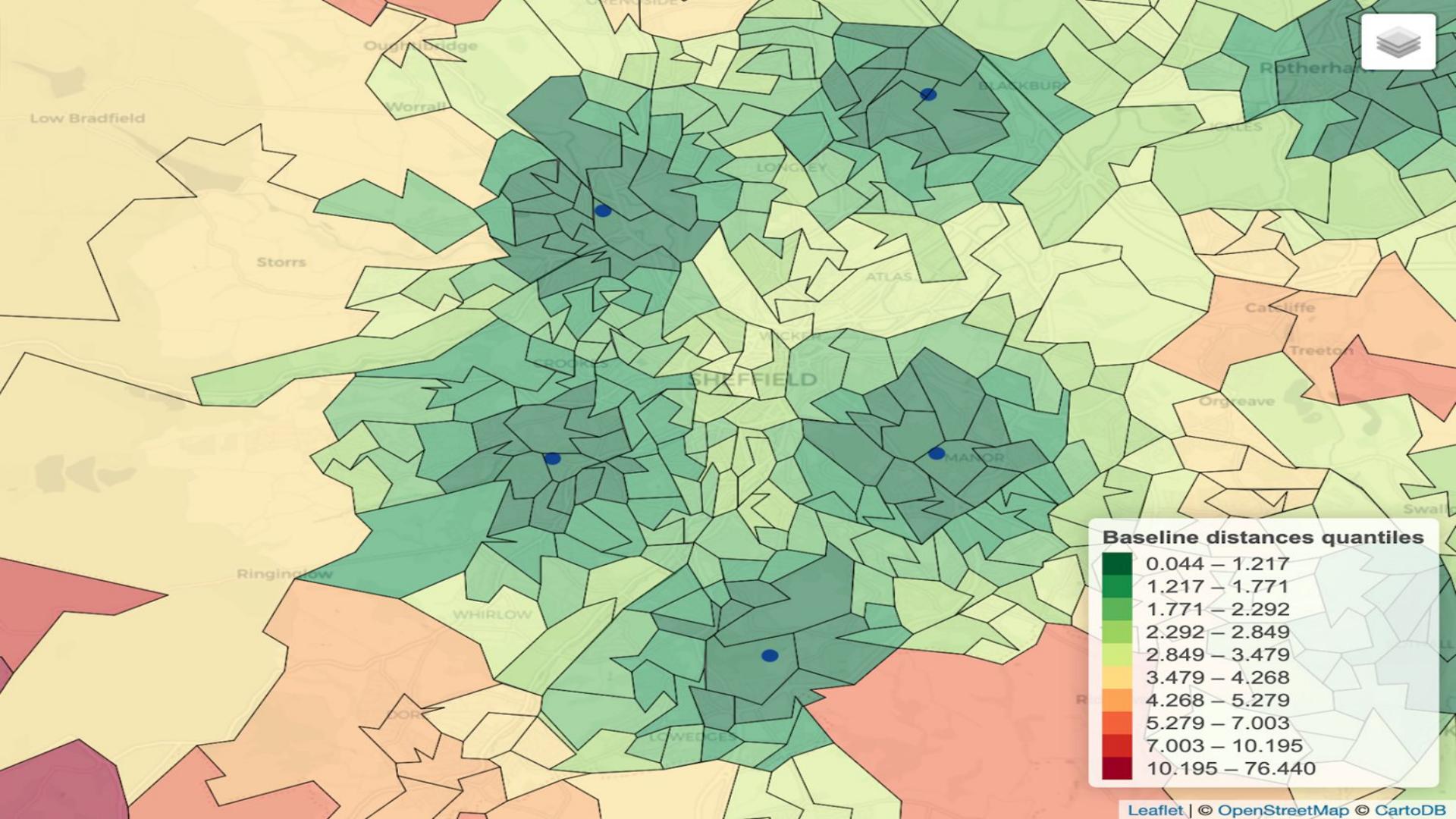
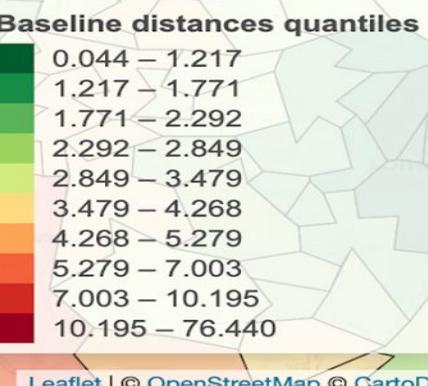


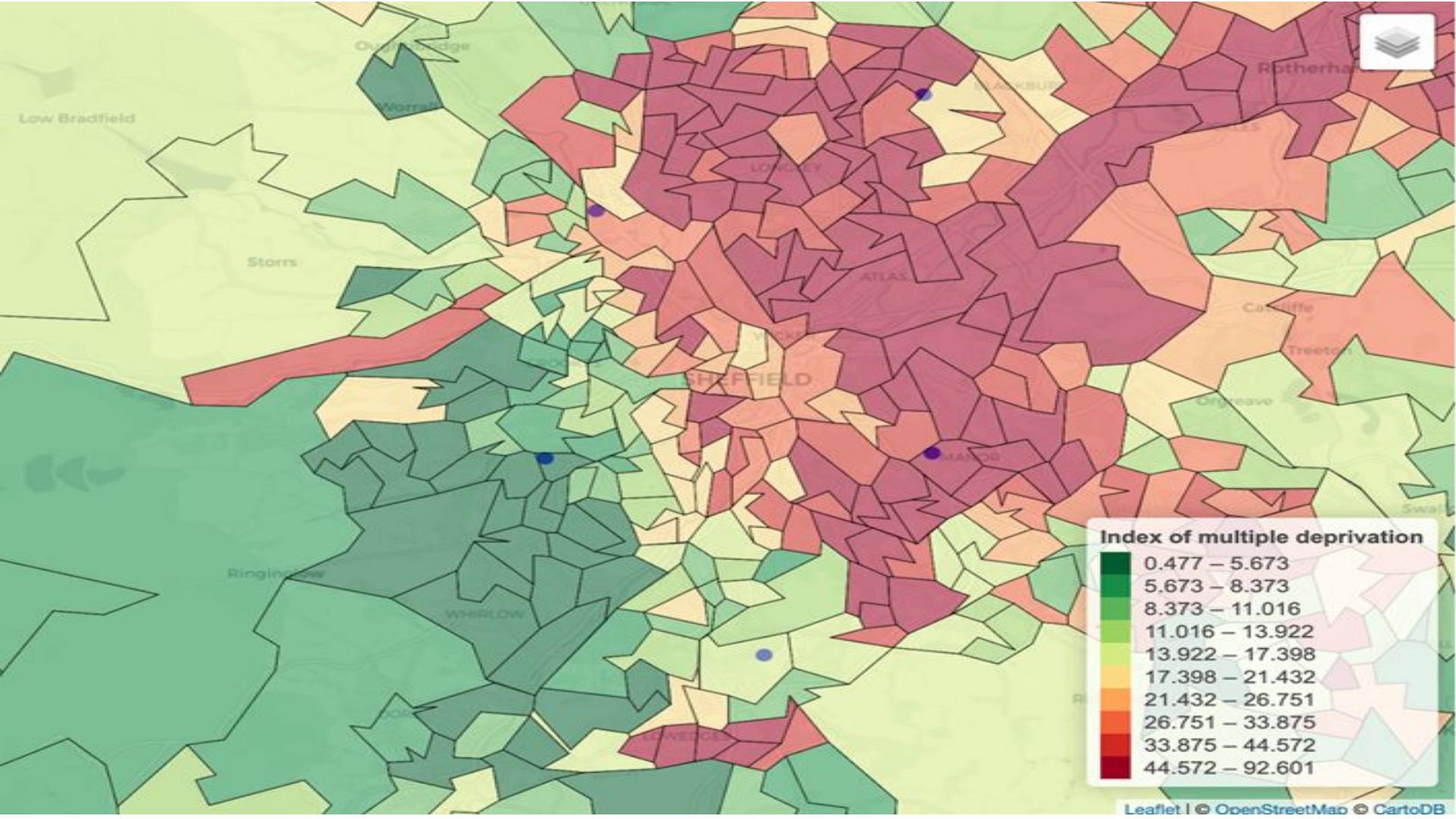


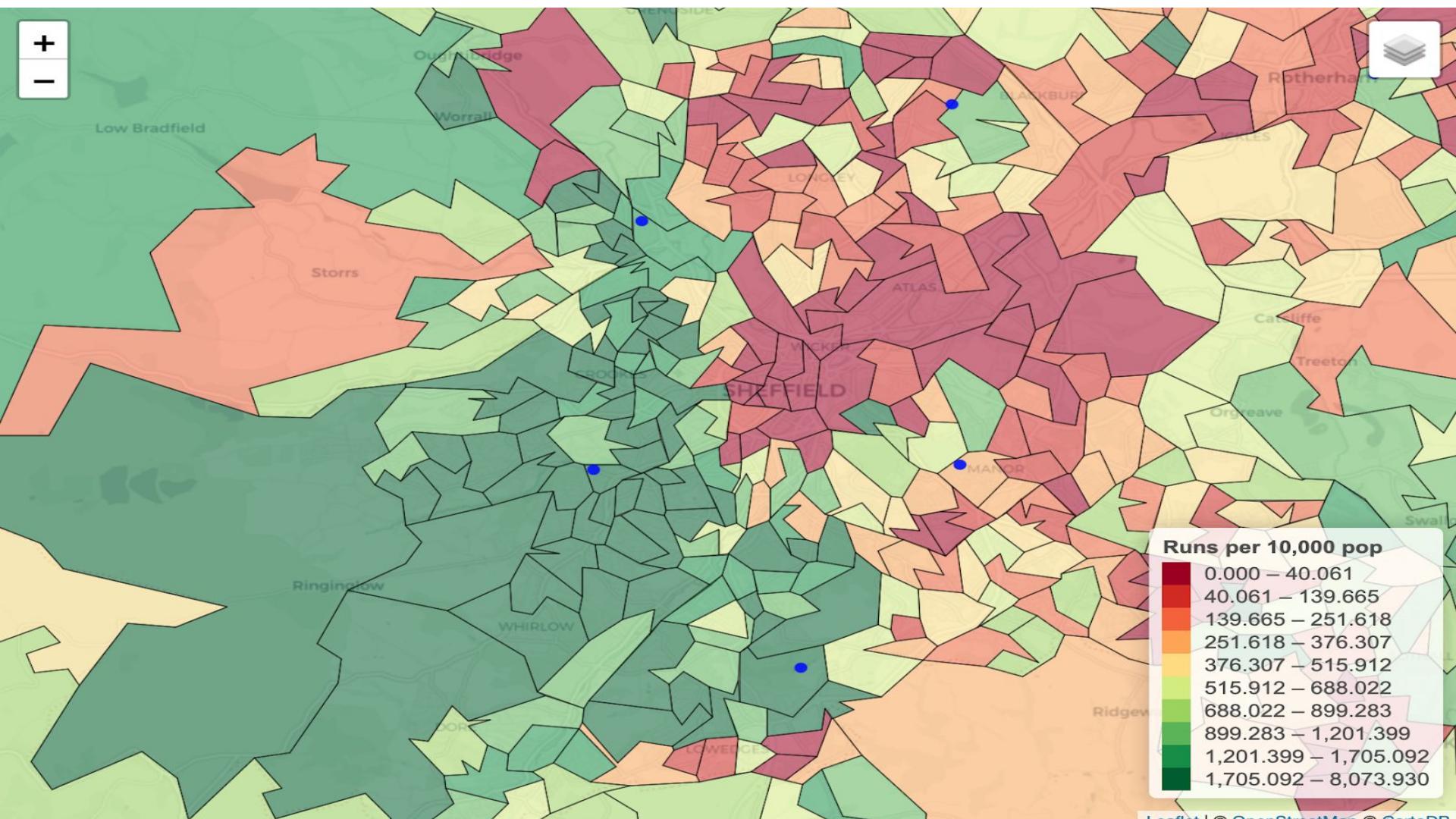
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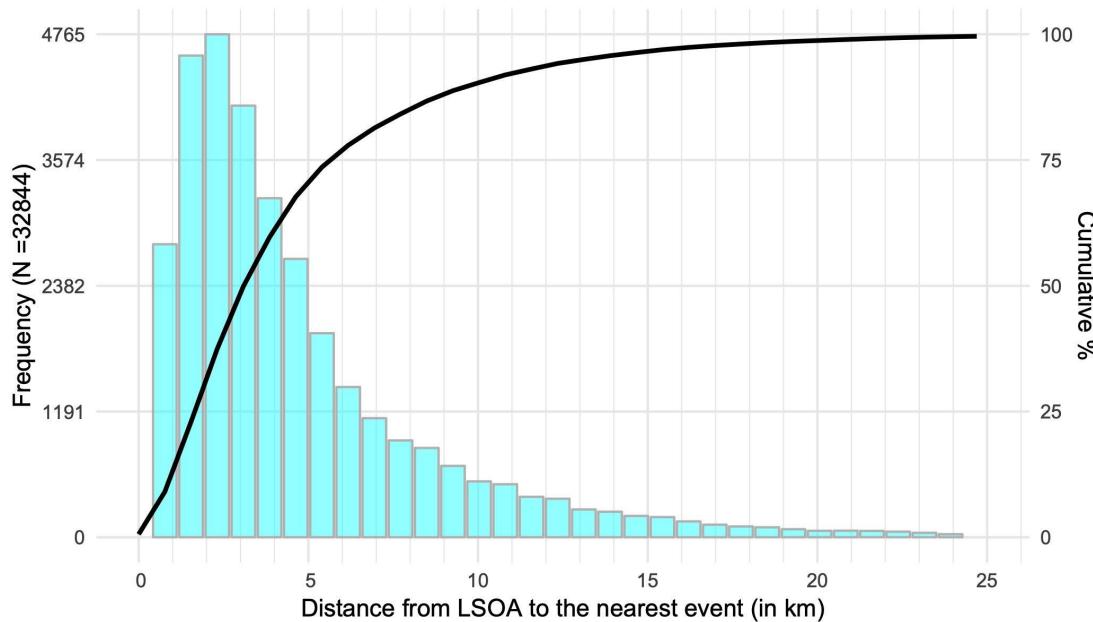






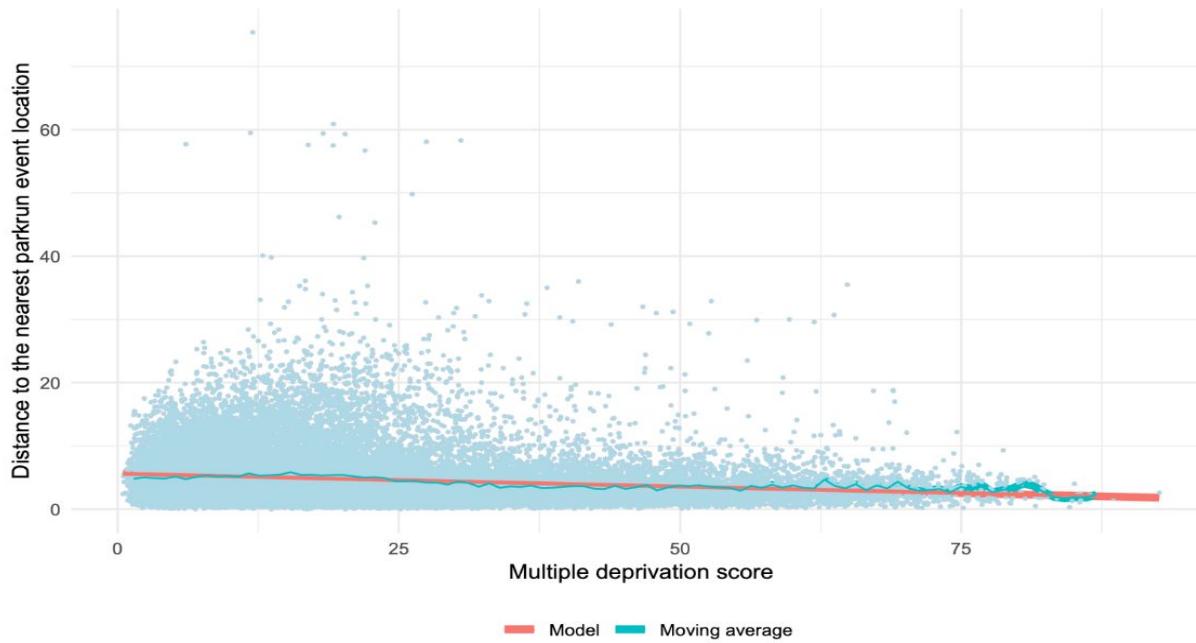
Results

1. How good is geographical access to parkrun?



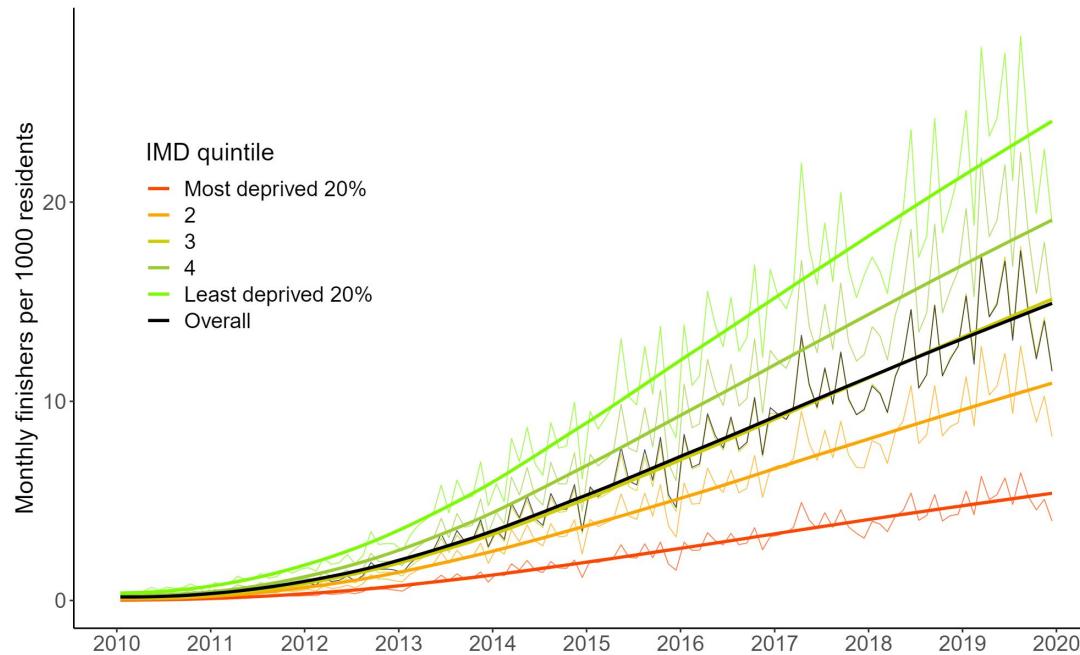
Results

2. How equitable is geographical access?



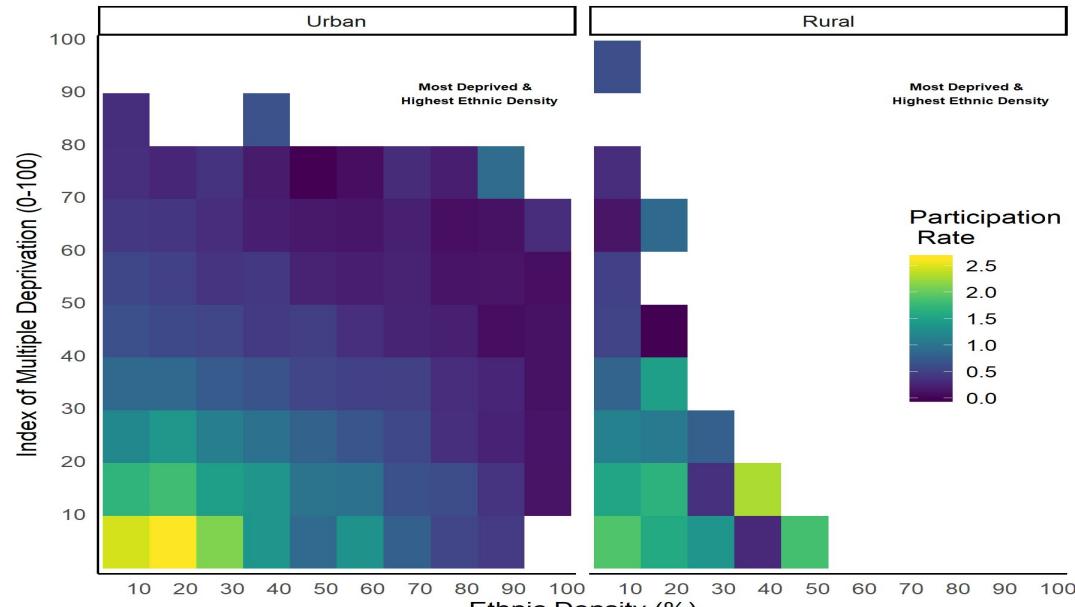
Results

3. How good is participation in parkrun?



Results

4. How equitable is participation?



Sources: Office for National Statistics
and parkrunUK

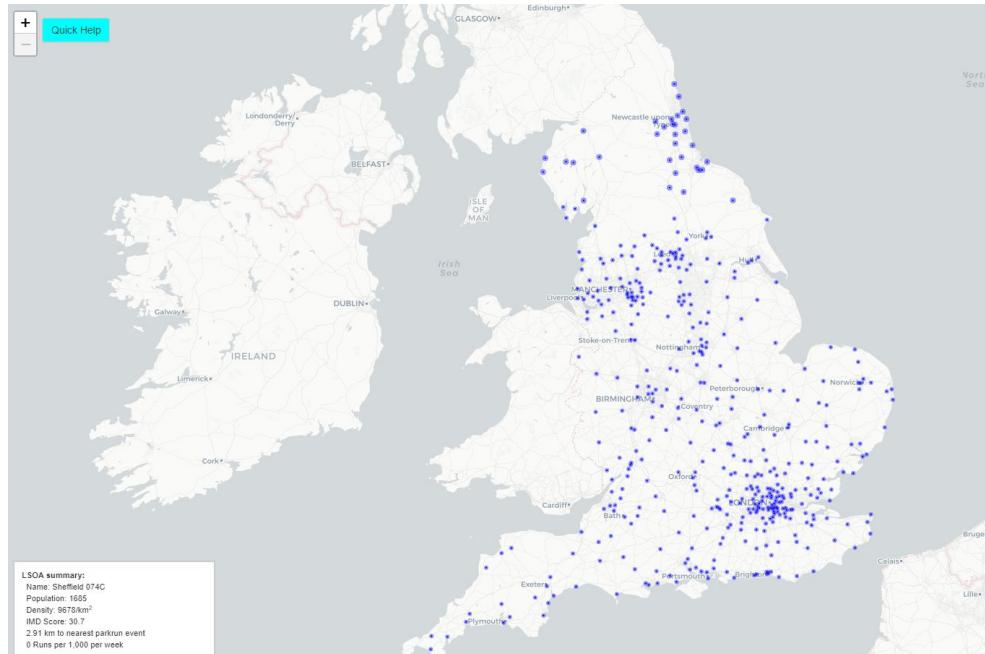
Where should parkrun locate 200 new parkrun events?



	Access	Participation
Efficiency	1. Maximize overall access.	3. Maximize overall participation.
Equity	2. Maximize deprivation weighted access.	4. Maximize deprivation weighted participation.

Results

Where should parkrun locate 200 new parkrun events?



<https://iolmap.shinyapps.io/parkrun/>

Pandemic Policy on 'parkrun' Participation

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BMC Public Health

RESEARCH **Open Access** 

The long-term effect of the coronavirus pandemic on parkrun participation: an interrupted time series analysis

Oscar Rousham¹ , Helen Quirk¹ , Elizabeth Goyer¹  and Robert A. Smith¹ 

Abstract

Background The growth of parkrun between 2004 and 2019 has been heralded as a success story for public health as a result of its physical activity and wellbeing benefits for participants. However, parkrun was not immune from the COVID-19 pandemic – with events in mainland England cancelled from March 2020 to July 2021. This study explores the lasting impact of the pandemic on parkrun participation to February 2023, and its implications across the socioeconomic spectrum.

Methods The study combines aggregated parkrun weekly finisher data from 32,470 Lower Layer Super Output Areas (LSOA) in England from January 2015 to February 2023 with Office of National Statistics (ONS) data on population and deprivation. Interrupted time series analysis using segmented Poisson regression models was used to estimate the immediate change in parkrun participation and the change in the rate of growth following the pandemic. Models were fitted for each Index of Multiple Deprivation (IMD) quintile separately to assess whether this effect differed by socioeconomic deprivation.

Results Visualisation and interrupted time series analysis showed a significant and long-term decrease in parkrun participation following the reopening of parkrun events. This was consistent across all IMD quintiles, indicating that the inequalities in parkrun participation according to IMD observed prior to the pandemic remained after the pandemic. Between March 2020 and February 2023, almost 13 million fewer parkrun finishes are estimated to have occurred relative to what would have occurred in the absence of the pandemic.

Conclusion The reduction in parkrun participation during the pandemic and following the reopening of events is likely to have negatively impacted wellbeing in would-be participants. Going forwards, policymakers must make the difficult trade-off between the long-term health and social implications of restricting outdoor physical activity events against the benefits associated with a reduction in infectious disease transmission.

Keywords Parkrun, Physical activity, Socioeconomic deprivation, Ecological study, Interrupted time series

Introduction

Engaging in regular physical activity is linked to a decreased risk of developing numerous non-communicable diseases [1], along with notable reductions in depression and anxiety [2]. However, a significant portion of the population falls short of recommended activity levels [3] and there is socioeconomic inequality in leisure time physical activity levels [1, 3, 19]. Elevating

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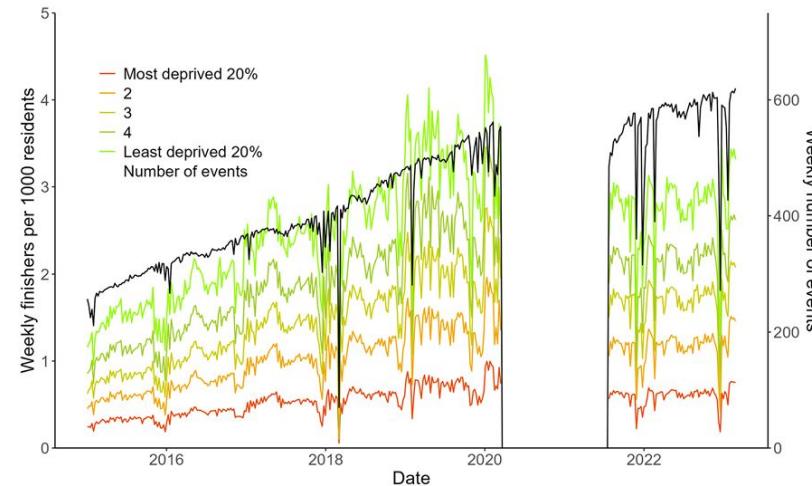


Fig. 1 Weekly number of parkrun finishers in England per 1,000 residents by Index of Multiple Deprivation Quintile, and number of parkrun events in operation, from January 2015 to February 2023

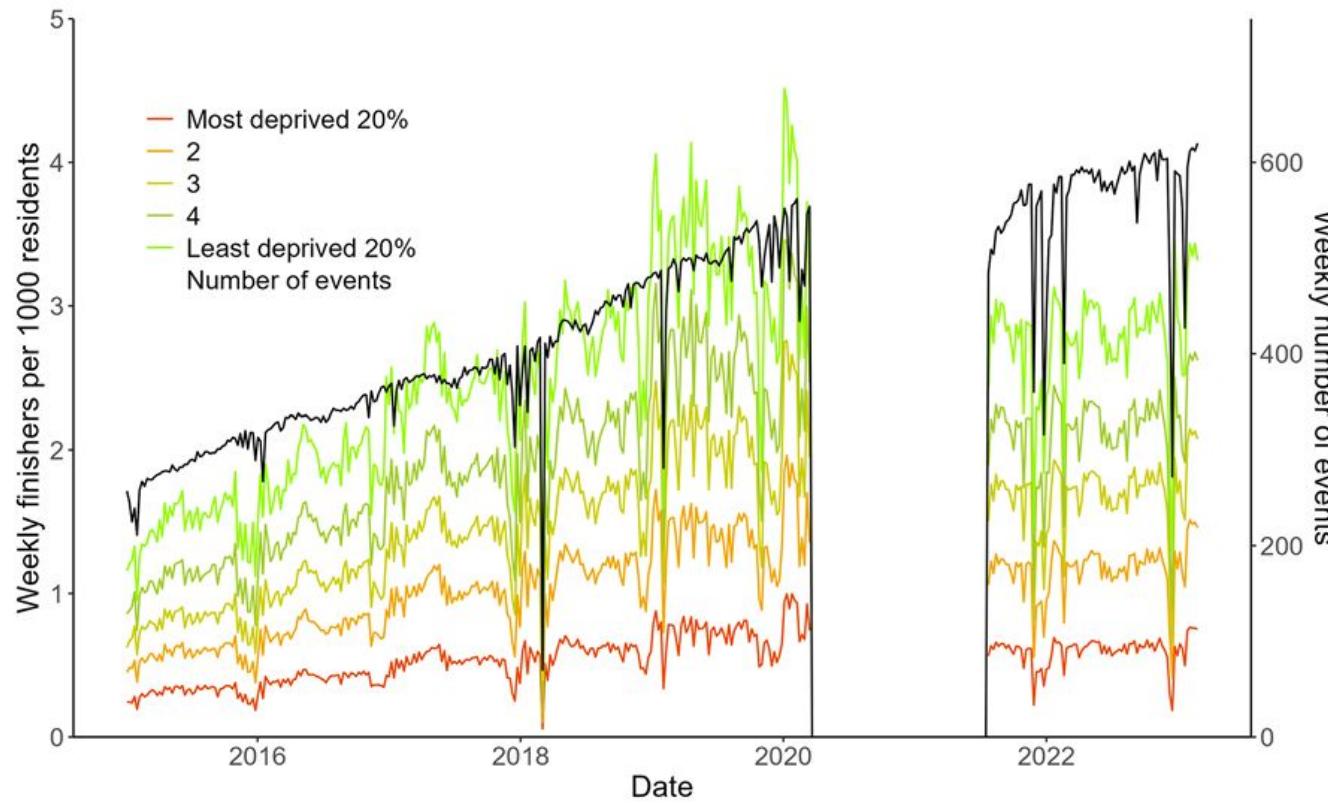


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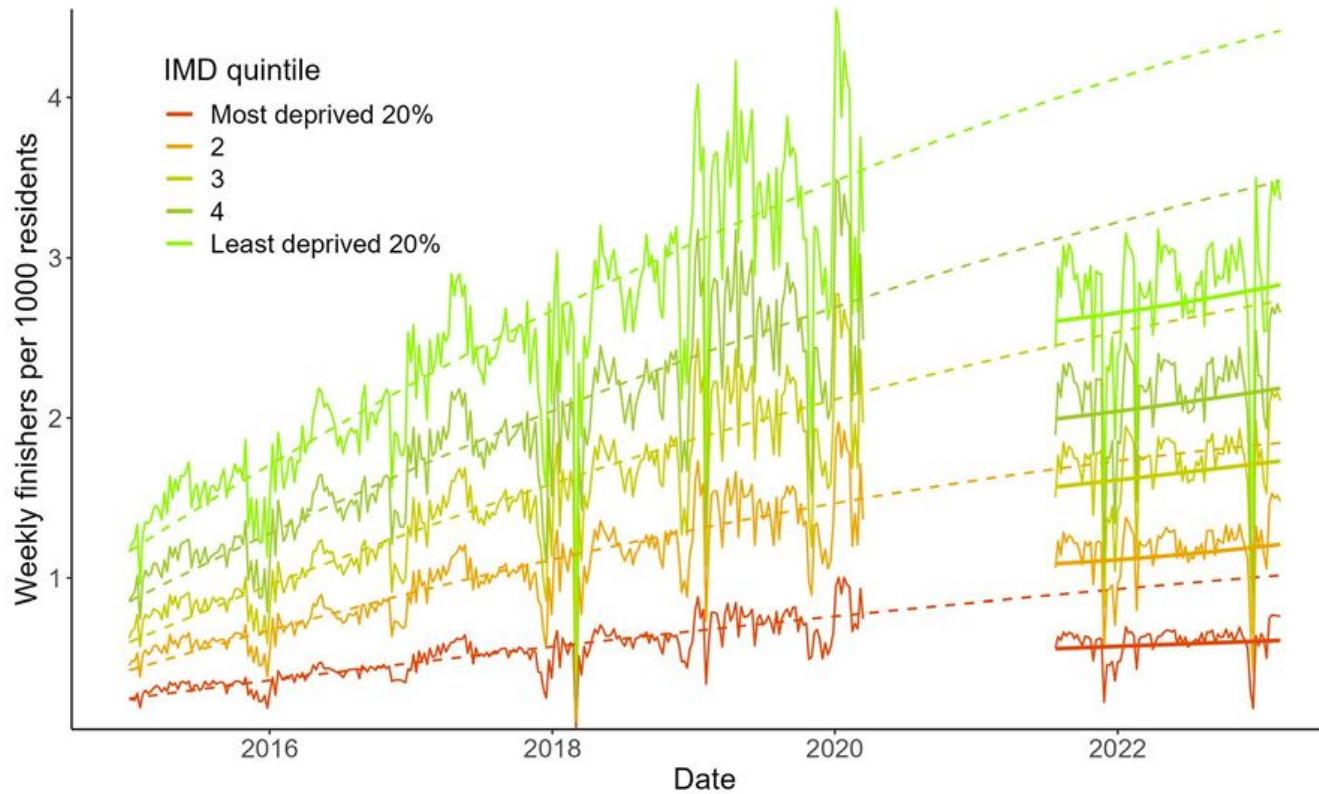


Fig. 2 Counterfactual (expected participation in the absence of the pandemic) compared to observed participation. The thin lines show the observed participation rates by IMD each week. The dotted lines show the pre-pandemic trend ignoring seasonal variation extrapolated across the study period. The solid lines show the post-pandemic trend, ignoring seasonal variation



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Having a great time at the [@N8CIR ReproHack](#)
reproducing the research in this really interesting
PrePrint about [@parkrunUK](#) by [@waq0r](#),
[@R06ertSmIth](#) and colleagues:

Does ethnic density influence community participation in mass participation physical activity events?

Authors: Robert A. Smith, Paul P. Schneider, Alice Bullas, Steve Haake, Helen Quirk, Rami Cosulich, Elizabeth Goyder

DOI: 10.12688/wellcomeopenres.15657.2

Submitted by rasmith3

Mean reproducibility score: 9.2/10 | Number of reviews: 5

Where should new parkrun events be located? Modelling the potential impact of 200 new events on socio-economic inequalities in access and participation

Authors: Schneider PP, Smith RA, Bullas AM, Bayley T, Haake SS, Brennan A, Goyder E

Submitted by hub-admin

Mean reproducibility score: 7.0/10 | Number of reviews: 3

<https://www.rephack.org/>



Open source & impact

“Rob and colleague Dr. Paul Schneider developed a statistical tool (an algorithm) which searched through all of the greenspaces in England and ranked the top 200 by predicted public health impact.

One example of how the statistical tool was used is the creation of Bowling Park parkrun, located in a deprived area of Bradford. Our local Ambassador, working with community groups, identified the location as an option for a parkrun event – which was corroborated by Rob’s work – and the event became a reality for the local people.” (parkrunUK, 2020).

<https://blog.parkrun.com/uk/2020/12/08/using-research-to-improve-inclusivity/>





Publications

Smith, R.A., Schneider, P.P., Cosulich, R., Quirk, H., Bullas, A.M., Haake, S.J. and Goyder, E., 2021. Socioeconomic inequalities in distance to and participation in a community-based running and walking activity: A longitudinal ecological study of parkrun 2010 to 2019. *Health & Place*, 71, p.102626.
<https://doi.org/10.1016/j.healthplace.2021.102626>

Schneider, P.P., Smith, R.A., Bullas, A.M., Bayley, T., Haake, S.S., Brennan, A. and Goyder, E. 2020. Multiple deprivation and geographic distance to community physical activity events — achieving equitable access to parkrun in England. *Journal of Public Health*. 48;53(189). <https://doi.org/10.1016/j.puhe.2020.09.002>

Smith, R., Schneider, P., Bullas, A., Haake, S., Quirk, H., Cosulich, R. and Goyder, E., 2020. Does ethnic density influence community participation in mass participation physical activity events? The case of parkrun in England. *Wellcome Open Research*, 5(9), p.9. <https://doi.org/10.12688/wellcomeopenres.15657.2>

Rousham, O., Quirk, H., Goyder, E. et al. The long-term effect of the coronavirus pandemic on parkrun participation: an interrupted time series analysis. *BMC Public Health* 24, 2931 (2024).
<https://doi.org/10.1186/s12889-024-20420-0>



Open Source Code

https://github.com/RobertASmith/DoPE_Public

https://github.com/RobertASmith/parkrun_temporal_23

https://github.com/RobertASmith/parkrun_temporal

<https://github.com/RobertASmith/parkruntimeseries>

https://github.com/ScHARR-PHEDS/iolmap_revision

https://github.com/ScHARR-PHEDS/parkrun_book



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Table of contents

- 1 Using this book
- 2 About the authors
- 3 Background
- 4 Introduction to R
- 5 Version Control
- 6 Intermediate R
- 7 Wrangling with data in R
- 8 Partitioned Survival Models
- 9 Cohort State Transition Models
- 10 Automated Reporting
- 11 Shiny for Health Economics
- 12 Advanced Data Visualisation
- 13 R Packages
- 14 Further Resources
- References

1 Using this book

Note from the authors: This work is a living document and is being adapted all the time based upon comments. New sections are being included prior to teaching. If you have suggestions for improving this book, please contact Robert Smith by email: rsmith@darkpeakanalytics.com.

— Dark Peak Analytics Teaching Team

This book was created to provide additional support for the taught course. It includes all of the code chunks, exercises and solutions which we cover in the taught sessions. It serves as a first point of reference, and directs the reader to additional resources. The book is written in R using the `bookdown` package, which converts each chapter from an RMarkdown file into a PDF or HTML book. Later in the course, we will cover how this process works.

There are currently thirteen chapters in the book, as shown in the table below. The content that is visible to you will depend on the scope of the course that you are enrolled on. For example those taking a course on the use of shiny for Cohort State Transition Models may have access to Chapter 7 and 10, whereas those doing an introductory R course may have access to chapter 1 only.